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TITLE: Large Vocabulary Audio-Visual Speech Recognition

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Large Vocabulary Audio-Visual Speech Recognition

Chalapathy Neti & Gerasimos Potamianos IBM T. J. Watson Research Center Yorktown Heights, NY 10598

- •Motivation
- •A/V speech recognition architecture
- ·Visual feature extraction
- Audio-visual fusion
- •Results
- Challenges and conclusions

Pervasive Speech recognition

- > Pervasive deployment of speech will require better recognition in degraded acoustic conditions:
 - High noise ("speech babble") e.g.
 - ✓ Military applications
 - ✓ Automobiles
 - ✓ Video Games & Interactive television 3



- · Whispered Speech
 - Privacy
- · Lombard speech
 - · High-noise conditions
- · Speech pathology



Audio-Visual speech recognition is a key enabler

IBM's A/V speech effort

- History (www.research.ibm.com/AVSTG)

 - About a 3 year old effort.

 Led the JHU Workshop team on A/V speech recognition, 2000.
 - AVSTG department formed in 2001
 - Taught an invited ELSNET tutorial on A/V speech recognition (Prague, 2001).
- Highlights/differentiators of our work
 - One of a kind database for AV LVCSR
 - State-of-the-art audio ASR subsystem (LVCSR) Fully automated visual front end

 - · Multiresolution face detection
 - Augmented visual speech ROI (jaw region instead of mouth)
 Multistage (linear transform based) visual feature extraction

 - Sub-phonetic visual speech models
 Scales to large-vocabulary recognit

 - Phone-level asynchronous A/V fusion

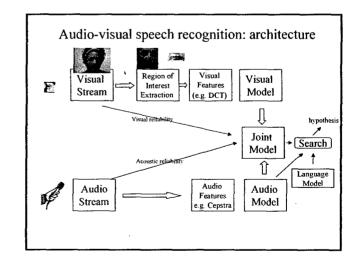
 Joint a/v model training

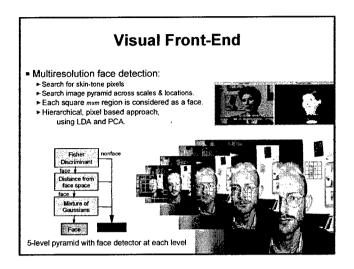
 Maximum entropy based stream weight estimation (global and local)

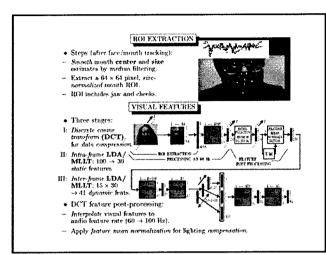
 - Multiple domain exploration

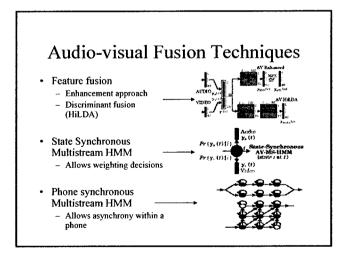
 Read speech (digits/C&C/L/CSR), Impaired speech, Automobile. Broadcast News

 Visual adaptation to new domains









THE MULTI-STREAM HMM FOR AV-ASR The multi-stream (MS) HMM: Observation conditional "acore" of audio visual state i → (i_n, i_s): £(y(t)|t) = {Pr(y_n(t)|i_n)}^{1,n} × {Pr(y_n(t)|i_n)}^{2,n} Exponents usoded stream "reflability". Typically: 0 ≤ λ_n, λ_n ≤ 1, λ_n + λ_n = 1 State vs. phone level synchronous (product) MS-HMM. State synchrony: (i_n) = (i_n) = (i_n + 1, i = i_n = i_n. State asynchrony: (i_n) = (i_n) × (i_n). MS-HMM parameter training: Model parameters: β = [θ_n, θ_n, λ_n, λ_n], where θ_n, θ_n are audio or visual-only HMM stream params. Maximum likelihood estimation (MLE) of θ_n, θ_n, via EM: a Independent E- and M-steps for MLEs of θ_n, θ_n. being addio-visual MS-HMM E-step. M-step as above. MLE of λ_n, λ_n is impossible. Instead, we have considered: β Paramete grid search. Minimizes held-out data WER. Minimum classification error (MCE) training by GPD. Maximum classification error (MCE) training by GPD. Maximum classification error (MCE) training by GPD. Maximum classification error (MCE) training by GPD.

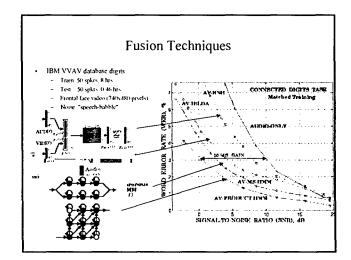
IBM VVAV databases

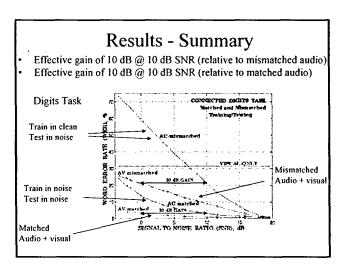
- LVCSR
 - First-of-a-kind audio-visual database for large-vocabulary continuous SI speech recognition (LVCSR)
 - 290 subjects
 - 70 hrs, continuous speech, 10.400 word vocabulary
- Digits
 - 50 subjects
 - 8 46 hrs, continuous speech, 11 word vocabulary
- · Database Format
 - Frontal face color video, 704x480, 30 Hz, MPEG2
 - 16 kHz/16bit pcm



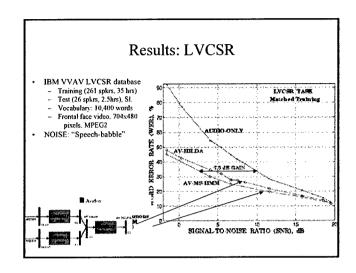


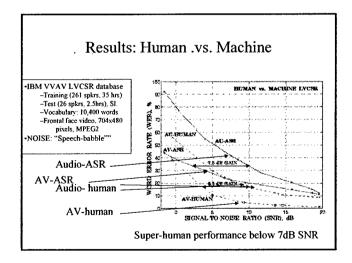
Experiments on Digits

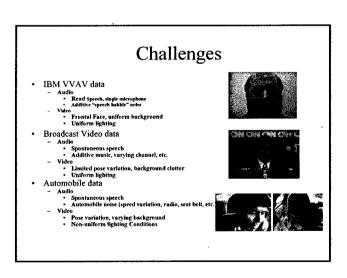




Experiments on LVCSR





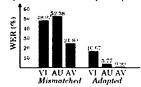


VISUALLY CHALLENGING DOMAINS: PRELIMINARY RESULTS Challenge: Video data variability in head pose, background, and lighting, affects face detection, HOI extraction/normalization, thus visual, and AV-ASR. Face detection error for VVAV, AUTO (multi-speaker vs. speaker-(in)-dependent) and BN data Visual-only WER for VVAV vs. AUTO domains (DIGTIS and IACSR tasks) DIGITS

AUDIO-VISUAL SPEAKER ADAPTATION

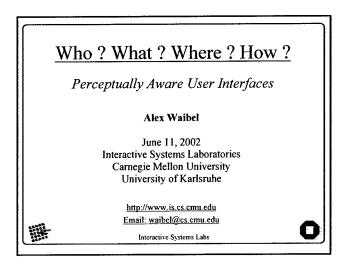
- Important for speaker empiliment and limited data domains, but hardly ever considered in the AY-ASR literature
- Main techniques:
 - MLLR: Rapid adaptation of HMM stream component mema-

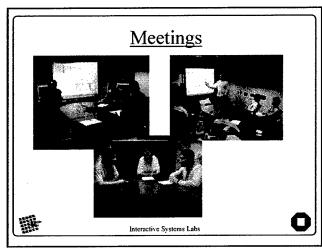
 - MAP: Bayesian approach, adapts all HMM parameters
 FE. Front end adaptation of LDA/MLLT matrices.
- The domains/tasks considered:
 - Domains: Noisy trading floor; hearing impaired speach
 - Tasks: IACSR; DIGITS.
- MLLR adaptation results on DIGITS speech impaired data:

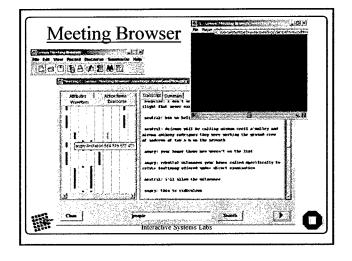


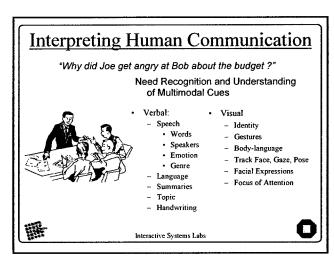
Conclusions

- · Consistent and significant gains for all audio conditions
- · Significant performance gains in "speech-babble" noise
 - Effective gain of 10 dB @ 10 dB SNR for digits
 - Effective gains of 7.5 dB @ 10 dB for LVCSR
- · Significant gains in relatively clean environments
 - 62% relative gain for digits (0.75 -> 0.28)
 - 8% for LVCSR
- Super-human performance at high-noise levels
- · Asynchrony modeling helps for digits
- · Further research required in visually challenging domains
- Visual adaptation is a promising approach
 - Upto 67% relative improvement in visual speech recognition





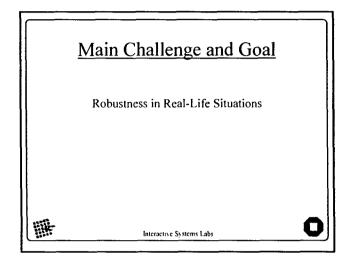


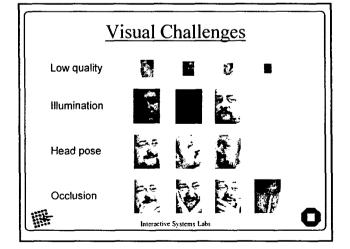


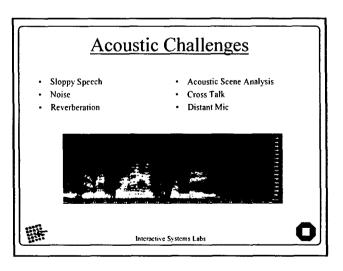


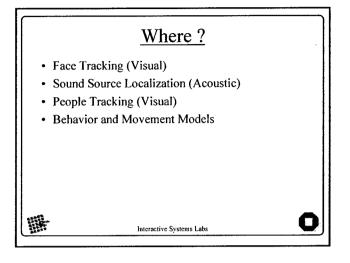
- People ID Who?
 - Speaker ID, Face ID
 - Type: Dominant. Submissive, etc.
 - Relationship: Family, Friends, Colleague
- Speech and Discourse What ?
 - Speech: Transcript
 - Discourse States (Speech Acts, Topics), Games, Turn Taking
 - Discourse Types and Genres (Negotiation, Chatting, Lecturing)
- · Emotional State, Affect How?
 - Angry, Happy, Sad, Afraid;... Busy, Nervous, Relaxed
 - Discourse Style: Sloppy, Formal, Colloquial
- Localization and Speaker and Focus of Attention Where?
 - Speaker Localization
 - Focus of Attention Tracking
 Interactive Systems Labs

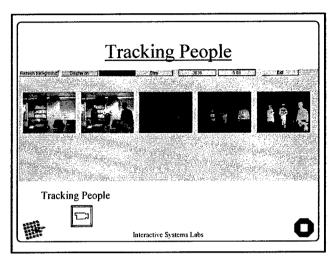


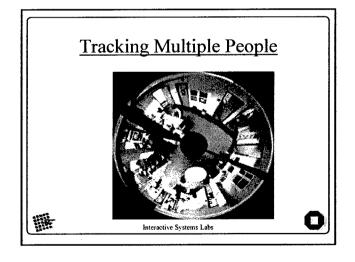


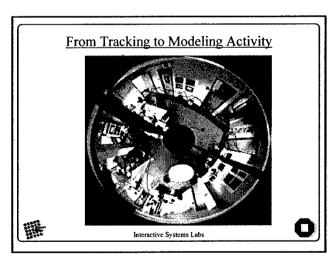


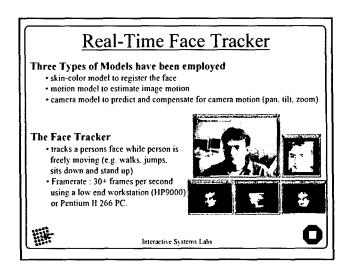




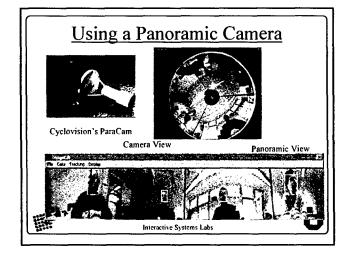


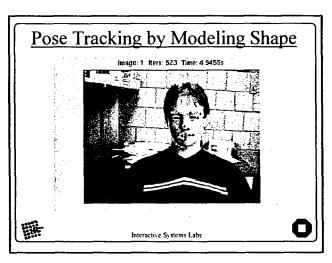


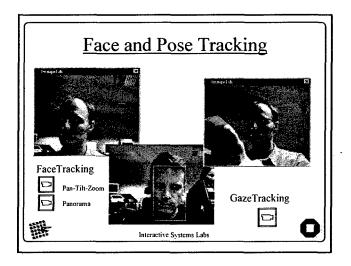














- · Large Vocabulary Speech Recognition
 - - · Sloppy Speech
 - · Distant Microphones
 - · Mismatch in Vocabulary
 - · Other Languages
 - Many Other Aspects: Topic Detection, Named Entity, Translation, Discourse,
- Multimodal Dialog
 - Fuse Speech, Pointing, Gesture, Handwriting
- Fusion Usually at Semantic Level
- Audio-Visual Speech
 - Combine Speech and Visual Info



From Read Speech to Conversational Speech

- · Wall Street Journal Dictation
- · Broadcast News Database
 - Transcription and Information Retrieval on News Casts
 - Multilingual Speech Recognition
- · Switchboard & Callhome
 - Human to Human Telephone Speech
- Meetings and Discussion Database
 - Newshour (18h)
 - Crossfire (9h)

Conversational Speech

- Group Meetings

Interactive Systems Labs

Transcribing Speech in Meetings

Interactive Systems Labs

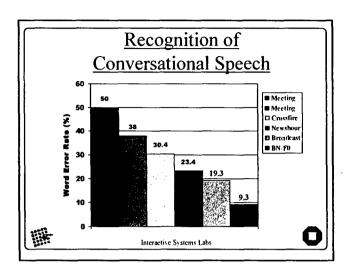
Run-On Transcription of Meetings

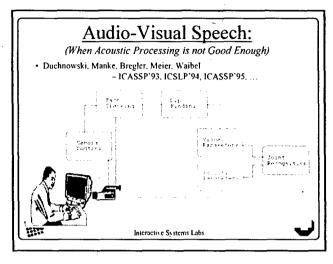
- Mismatched Recording Conditions
 - Remote Microphones
 - Cross-Talk
 - Recording Always on !
 - Noise
 - Multiple Speakers
- Mismatched Speaking Style:
 - Spontaneous and Conversational Human to Human Speech
 - Emotional Speech
- Mismatched Language and Vocabulary
 - Special Ideosynchratic Topic

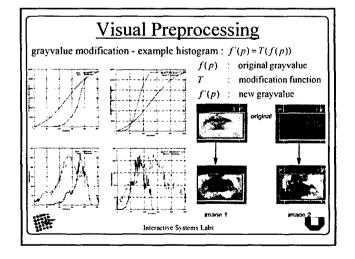


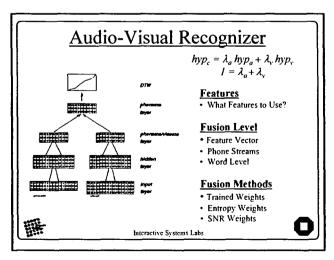


- · Three Tasks:
 - Newshour
 - Crossfire
 - Group Meetings

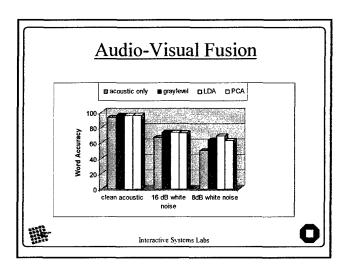


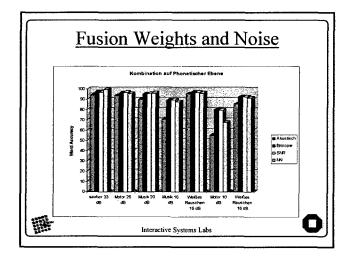


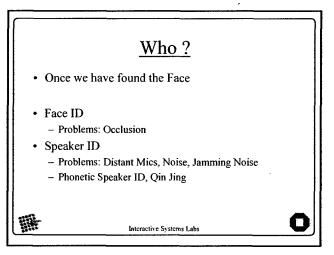


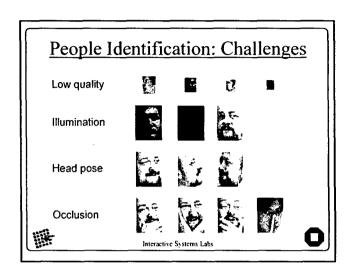


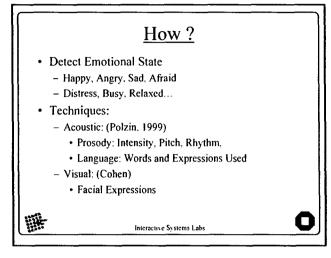
Experiments - Task: Continuous Letter Spelling - Difficult, but smaller Vocabulary - Speaker dependent audio-visual results - Fusion by Entropy Weights - LDA Front End - Phone Level Fusion

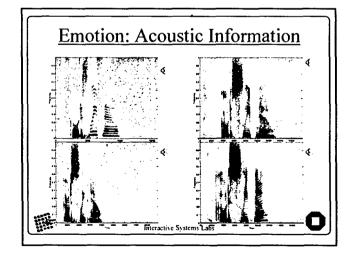


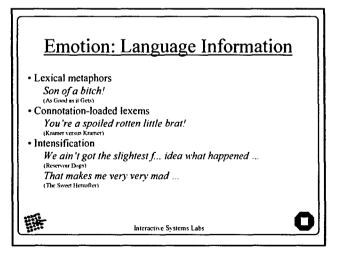


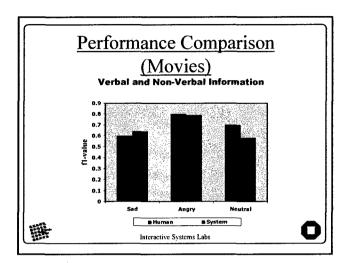










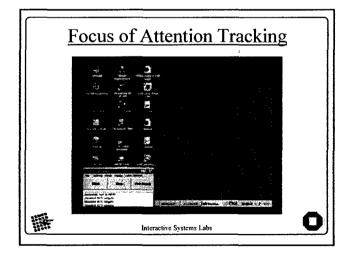


To Whom?

- Focus of Attention Tracking
 - R. Stiefelhagen, PUI'98, Humanoids'01, PhD Thesis'02
 - Who is addressee of an utterance?
 - Who is someone making talking to?
 - What is a human user attending to ?
- · Observation:
 - FoA is a Psychological State, can only be infered or 'guessed' from correlates
 - Both Observed User and Target are important:
 - Pose, Eye-Gaze
 - Possible Targets: Noise, Movement, Faces, Speech



Interactive Systems Labs



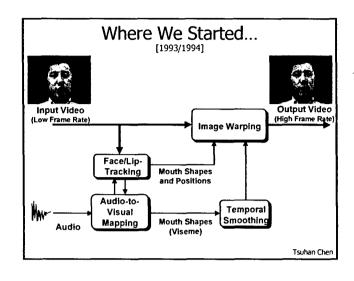
Conclusion

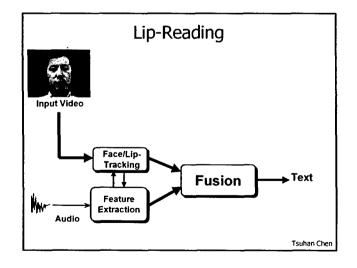
- Complete Model of Human Communication is Needed
 - Include all modalities
 - Include different not only what was said, but also:
 who, where, to whom, how...
- · Challenges:
 - Robust Processing of Component
 - Proper Level and Method of Fusion
 - Robust and Dynamic Fusion of Useful Clues

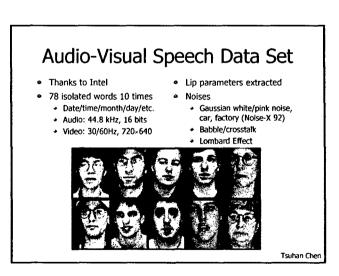


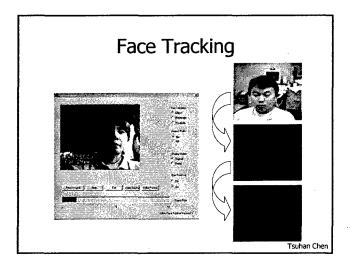
Interactive Systems Labs

Joint Audio-Visual Speech Recognition and CMU Audio-Visual Speech Data Set *Prof. Tsuhan Chen* Carnegie Mellon University Thanks to Dr. Simon Lucey and Jle Huang









Lip Tracking

- Modeling color distribution of mouth pixels
 - → Gaussian mixture
- Deformable template







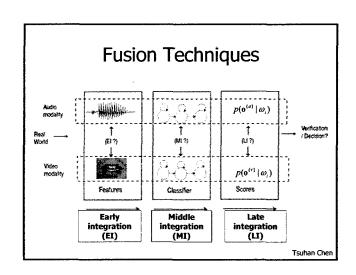
Tsuhan Cher

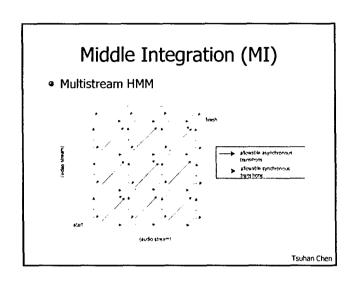
Customers...

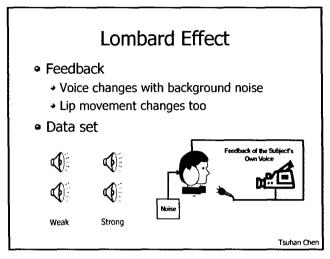
- "Signal Processing for Media Integration," ICASSP 2002
 - → Coupled HMM for Audio-Visual Speech Recognition, Nefian et al., Intel
 - Visual Speech Feature Extraction for Improved Speech Recognition, Zhang, Mersereau, Clements, Georgia Tech
 - Audio-Visual Speech Modeling Using Coupled HMM, Chu, Huang, UIUC
- Others

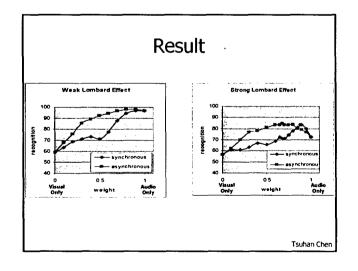
California State University Chunghwa Telecom Lab, Taiwan DongYang University, Korea Fabbrica Servizi Telematici, Italy IIT Bombay, India Instituto Tecnologico de Buenos Aires On2.com Queensland University of Technology National Tsinghua University National University of Singapore Norwegian Computing Center, Norway Shanghai JiaoTong University, China Washington University

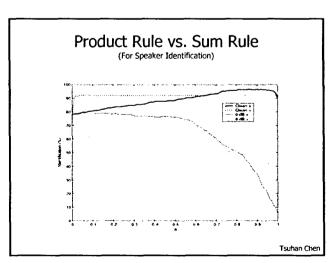
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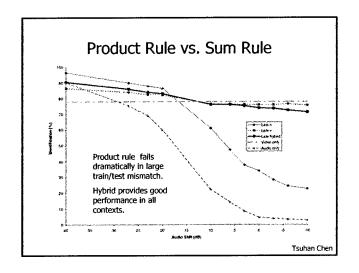










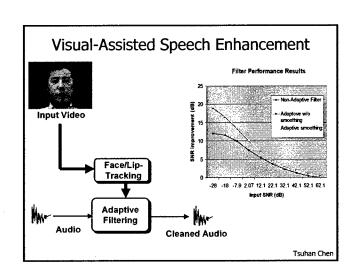


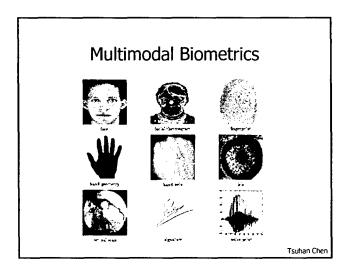
Quick Recap

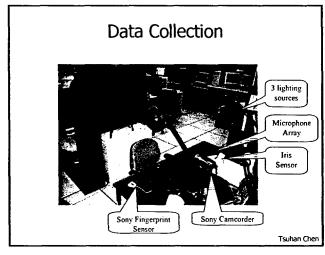
- Asynchronous MI (LI) has more freedom than synchronous MI (EI) → Better performance
- Product rule is better in Bayesian sense, but sum rule is more robust to mismatch
- Robustness to weighting
- Need to be careful about Lombard Effect
- · Key to multimodal fusion
 - To model dependency between audio and visual signals
 - To dampen independent audio and visual noises

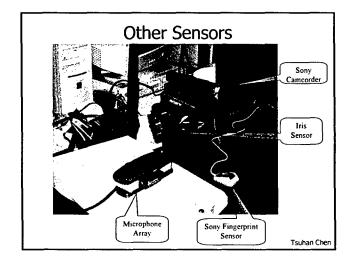
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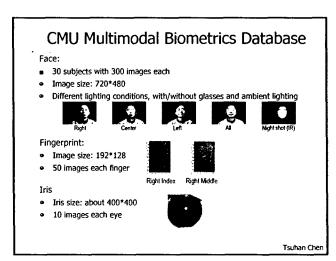
Beyond Multimodal ASR...

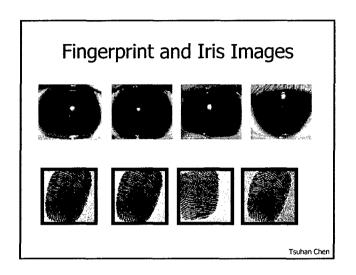


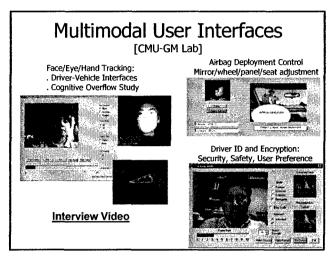


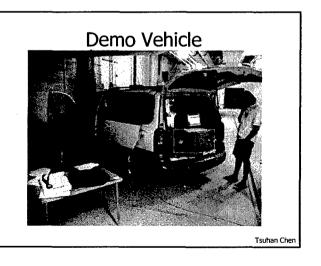


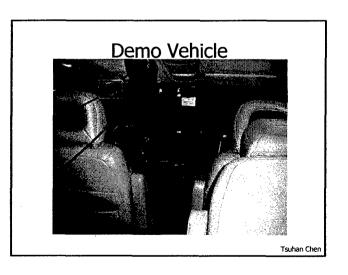


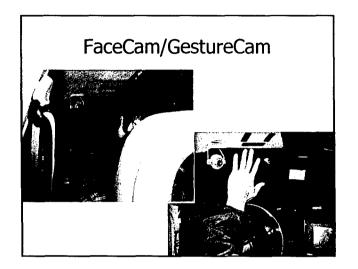






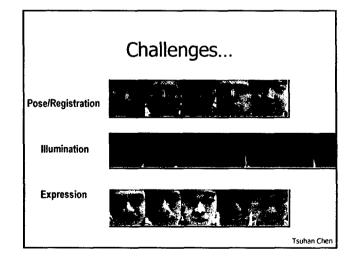


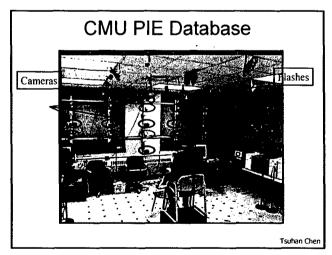


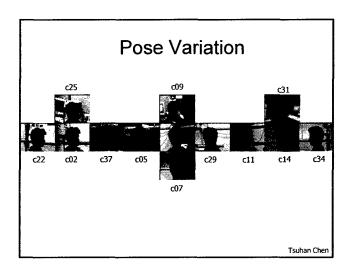


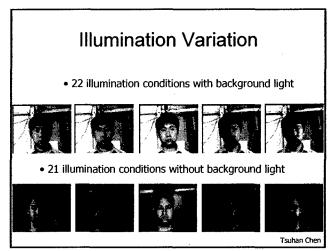
"Visual is not noise-free"

Tsuhan Chen









Conclusions

- Database is essential
 - → Need to consider Lombard Effect
- Fusion is important
 - ◆ We can learn from acoustic ASR; we can perhaps lead ASR
- · Confidence estimation is important
- Visual channel is not noise-free

Tsuhan Chen

Related Forums

- IEEE Multimedia Signal Processing (MMSP) Technical Committee, 1996~
- Proceedings of IEEE, Special Issue on MMSP, 1998
- IEEE MMSP Workshops
 - Princeton 1997, Los Angeles 1998, Copenhagen 1999, Cannes 2001, St. Thomas 2002
- $\bullet\;$ IEEE International Conf. on Multimedia and Expo. (ICME)
 - New York 2000, Tokyo 2001, Lausanne 2002, Baltimore 2003
- IEEE Transactions on Multimedia, March 1999~
 - Special issues: networked multimedia 2001, multimedia database 2002, multimodal interface 2003

Tsuhan Cher

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Please visit us at:

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Or, please email me at tsuhan@cmu.edu

Tsuhan Chen